Crop Yield Estimation Using NOAA − AVHRR Data and Meteorological Data in the Eastern Wimmera (South Eastern Australia)

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ABSTRACT

Having an estimate of final yield early in the growing season can be a powerful management and economic tool for the farming community. Therefore the possibility of using temporarily high resolution remote sensing data in combination with daily meteorological data for crop yield prediction on a close to field scale has been investigated for one of the main cropping areas in south−eastern Australia. The lack of rainfall in semi−arid to semi−humid climate of this region is one of the major limiting factors to crop growth. The relation of different parameters, such as the "Normalized Differential Vegetation Index" (NDVI), the date of the commencement of the grainfilling stage (GF), the water−Stress Degree Days" index (SDD), as well as the growing season rainfall, to yield of canola, wheat and cereals (wheat and barley) have been examined. Using information from 1995 to 1997, a crop yield estimation model on the basis of a multiple linear regression model has been developed and evaluated. The following paper reports the results of a study carried out at the Commonwealth Scientific and Industrial Research Organization (CSIRO), Aspendale, in collaboration with the Department of Natural Resources & Environment (NRS), Melbourne, and the University of Munich.

1. USING REMOTELY SENSED DATA FOR CROP YIELD FORECASTING AS AN AGRICULTURAL MANAGEMENT TOOL

For farmers in the eastern Wimmera (Victoria, Australia) it is important to estimate final yield early in the growing season. Using their knowledge and experience about the local conditions they are able to estimate yield to a certain extent. Having reliable predictions of yield on a close to paddock scale could support their management and economic decisions.

A basic parameter for crop yield, especially in semi−humid to semi−arid regions is growing season rainfall (GSR). Therefore, the GSR is often used by farmers to estimate final yield. Also, remotely sensed data have proved to be a good source of information for agricultural applications, in particular for yield estimation. Amongst others, M. S. RASMUSSEN (1997) and S. MOULIN et al. (1998) give a good review over past and present trends.

One of the most common approaches is the use of vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) as a measure for plant growth and development. M.S. RASMUSSEN (1992) examined the integral of NDVI from data of the Advanced Very High Resolution Radiometer (AVHRR) over the phenological stages of reproduction of wheat for 4 km² areas. N.A. QUARMBY et al. (1993) also investigated AVHRR−data and created 4 years time−series of NDVI. They point out the importance of the grainfilling period of wheat for final yield. M.P. CABEZÓN and J.C. TAYLOR (1994) analyzed correlations of multiple linear regressions using variant combinations of rainfall parameters and vegetation indices as independent variables. R.C.G. SMITH et al. (1991) found, that in a mediteranean−type environment the vegetation index − yield relationship does not explain yield variations significantly better than the rainfall − yield relationship over the growing season. However, they also point out that a combination of such information in a multiple linear regression model do improve the correlation significantly.

Since S.D. JACKSON et al. (1977) it is known, that observations in the thermal band of the EM−spectrum can be used as an indicator for the plants' water−stress. They use the difference of observations of daily surface temperature and air temperature for deriving the water−stress index "Stress Degree Days" (SDD).

To better take into account the course of vegetation development, temporarily high resolution remote sensing data have to be applied. Only frequent observations allow the examination of the crop's response to changing agrometeorological conditions. Such data can be obtained from the AVHRR−sensor onboard the polar orbiting satellites of the NOAA−series. The high temporal resolution, however is at the expense of the spatial resolution. The AVHRR−sensor has a spatial resolution of 1.1 km in nadir at a temporal resolution of one daytime overpass. One of the objectives of this research was to take advantage of the AVHRR's high temporal resolution at the largest possible scale. Another objective was to develop a method to predict crop yield, that meets the requirements of the local farmers in the Eastern Wimmera.

2. DATABASE

2.1. The AVHRR−Data

A system summary of the AVHRR−sensor is given on the World Wide Web site of NOAA's polar data user guide (NOAA POD Guide). Observations by the NOAA−14 were used exclusively.

Data for the growing seasons of the Eastern Wimmera (May to December) from 1995 to 1997 were processed using CSIRO standard routines for calibration navigation, geometric correction and cloud masking (DILLEY, A.C., ELSUM, C.C. (1994), DILLEY, A.C., EDWARDS, M. (1998)). The short−wave channels 1 and 2 (see table 1) were used for calculating the NDVI,

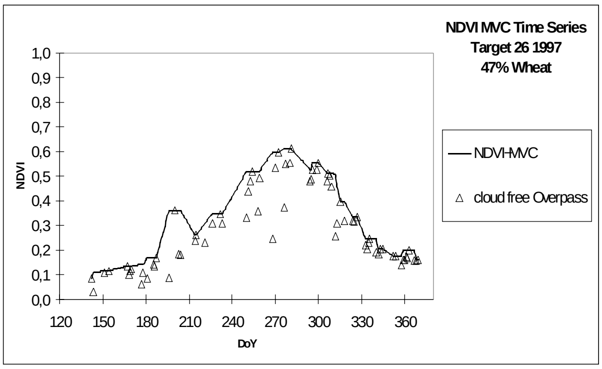
Table 1: Spectral Bands of the NOAA−14 AVHRR (http://www.ncdc.noaa.gov).

Channel #	Band width [µm]	Spectrum
1	0.58–0.68	VIS red
2	0.73–1.10	NIR
3	3.55–3.93	MIR
4	10.3–11.3	TIR
5	11.5–12.5	TIR

$$NDVI = (Ch2 - Ch1) / (Ch2 + Ch1) \qquad (1).$$

For atmospheric correction a maximum value composite (MVC) technique was applied to the NDVI time series (see e.g. B.N. HOLBEN (1986)). For daily values, NDVI was interpolated linearly between the cloud free observations. Figure 1 shows the MVC of NDVI of a 3*3 pixel subset (47 % of the area was wheat) in 1997. It represents the typical course of the NDVI−MVC of wheat in 1997. This is also valid for the sudden decrease around day of the year (DoY) 210, which was due to drought. The size of single paddocks in the Eastern Wimmera is usually in the order 1 km². 3*3 pixel subsets, thus guarantee that the paddock of interest is covered by the observation subset at the estimated geometrical accuracy of one pixel (DILLEY, A.C., ELSUM, C.C. (1994)). In the AVHRR channels 4 and 5, thermal infrared radiance emitted by the earth−atmosphere system is measured. The atmosphere's influence was removed using a split window technique (e.g. refer to A.J. PRATA 1994). As split window coefficients, those determined empirically by A.J. PRATA (1994) for wheat paddocks in south−eastern Australia were applied. Coefficients were available for "bare soil", "maximum green vegetation cover" and "mature crop". Within the NDVI – MVC curvature, the bare soil signal corresponds to the low NDVI at the beginning of the growing season, after sowing and before emergence; maximum cover corresponds to the maximum NDVI occurring and mature crop corresponds to a NDVI value just before harvest, early in December. Y.H. KERR et al. (1992) describe how to use the NDVI signature for deriving split window coefficients adapted to the changing states of plant growth by calculating the fraction between two stages and re−calculating the coefficients using this fraction. This idea was applied to the data of the Eastern Wimmera. Thus, a good approximation of daily land surface temperatures was available.

Figure 1: NDVI − MVC time series for the 3*3 pixel target ID 26 1997 47% wheat.



2.2. Meteorological Data

The weather data used, was made available by the Australian Bureau of Meteorology (BoM), situated in Melbourne. Information applied was daily maximum, average and minimum temperatures from three stations and daily rainfall from seven stations within or close to the study area. To approximate the meteorological conditions within the targets, spatial interpolation between the station was carried out. As there was no significant spatial variation in temperature, nearest neighbor interpolation was sufficient. Rainfall, however, had a very high spatial variability, so the data had to be interpolated using the inverse of the squared distance as a weight.

2.3. Yield Data

Yield data were obtained directly from the farmers by questionnaires. The farmers are able to derive such information on paddock scale during harvest from the amount of crop they sell, transport or store. This data can be regarded as accurate and reliable.
Wheat, Barley and Canola are the main crops in the Eastern Wimmera. Due to the large size of the observation targets (approx. 9 km²), several crop types can be found within one target and most of the times their composition was only known to a certain extent. Therefore, areas to be included into the prediction model had to show uniform behavior in space and time. This was tested by examining the variations in time and space between smaller and larger subsets around the center pixel of the subset throughout the observation period.

3. MODEL DEVELOPMENT

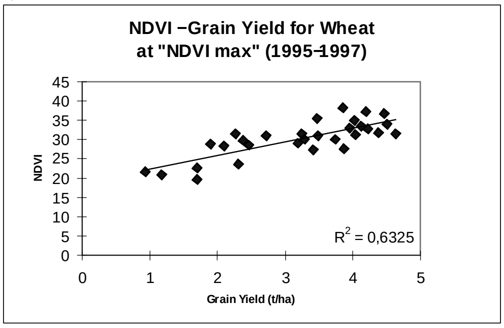
3.1. Prediction Dates

The timing of the predictions is very important for the applicability of the prediction model as a management tool. The farmers need reliable and timely forecasts to take management actions. The growing season of wheat in the eastern Wimmera lasts from May to December; this means that predictions should be made available throughout the growing season until the end of October, when there is the last opportunity to take economic decisions (personal communication with the farmers). Predictions before September proved not to be reliable. Thus, three prediction dates were tested: 10.September (DOY 253), just in time for taking additional management actions, NDVI(max), at maximum green vegetation cover (usually between end of September and Mid of October, ca. DOY 265 to 290) and 31.October (DOY 304), as the latest date for taking final economic decisions (e.g. insurances).

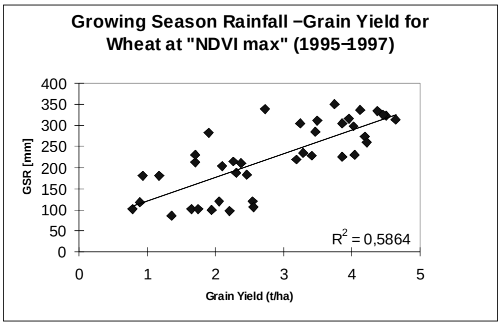
3.2. Single Linear Regressions

Figure 2: Linear regressions of cumulated NDVI, GF, GSR and cumulated SDD for the growing seasons 1995 to 1997 of wheat at the prediction date "$NDVI_{max}$.

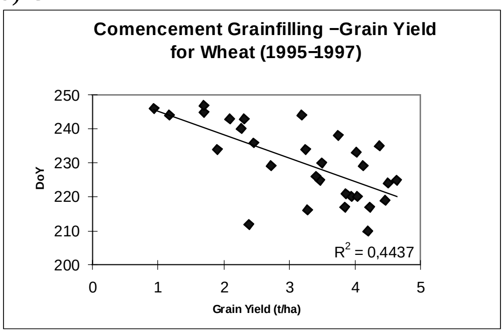
a) NDVI



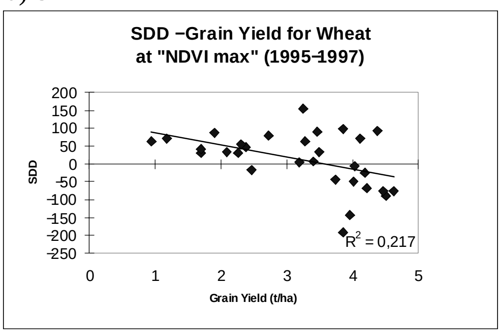
c) GSR



b) GF



d) SDD



The yield data's correlation to four parameters was examined: Cumulated daily NDVI from May, 1st to the prediction date (NDVI), the date of the commencement of the grainfilling stage (GF) as a measure for the duration of the grainfilling, daily rainfall cumulated from May, 1st to the prediction date to indicate the growing season rainfall (GSR) and the water stress index "stress degree days" (SDD), cumulated from July, 1st to the prediction date. Figure 2 shows the linear regressions of those parameters with yield of wheat for 1995 through 1997. Cumulated NDVI (Fig. 2a), as an indicator for green vegetation growth, has a positive correlation with crop yield. The offset of the regression line is due to the NDVI caused the by soil background. The GF parameter (Fig. 2b) can be identified from the NDVI – MVC curvature (figure 1). The maximum of the NDVI usually is not one sharp peak, but is situated within a more or less broad plateau of high NDVI values (see figure 1). The plateau very well corresponds to the grainfilling stage of wheat, when green leaf biomass is at a maximum (i.e. NDVI is at a maximum) and all the photosynthetical production is used for filling up the ears (N.A. QUARMBY et al. (1993)). The GF parameter has a negative correlation with yield. The earlier it starts, the longer it can last, and the more grain yield can be expected. The commencement of the grainfilling stage was approximated by the first day, when the NDVI was greater than 0.5. GSR (Fig. 2c) has a positive correlation with yield. The offset can be interpreted as the minimum rainfall necessary for yield greater than 0 in the growing season, assuming a strict linear regression. The SDD water stress index is calculated as the difference between surface temperature (here: from AVHRR measurements) and air temperature (here: as measured at 3 pm). This index was first described by R.D. JACKSON et al. (1977). Negative values correspond to a surface temperature lower than the air temperature due to the transpiration of plants. When transpiration is reduced because of drought, the surface temperature increases and so does the SDD. Positive values are interpreted as water stress. Figure 2d shows the negative correlation of SDD with crop yield. The relationship in this case is not very strong, but yet significant. It becomes stronger with late prediction dates (not shown here).

Table 2 shows the squared correlation coefficients for all prediction dates examined for wheat. All correlations were found to be significant on a 95 % level. Nevertheless, none of the regressions for themselves are reliable enough to allow accurate and reliable yield estimations.

Table 2: Squared Pearson correlation coefficients for different parameters to yield of wheat at three prediction dates using data from 1995 to 1997. GF generally appears after September, 10th.

95-97				
Date	NDVI	GF	GSR	SDD
10. Sep.	0.4204	n/a *	0.4639	0.37201
NDVI max	0.6325	0.4437	0.4875	0.217
31. Oct.	0.497	0.4437	0.3544	0.59556

3.3. Multiple Linear Regressions with Crop Yield

A multiple linear regression model for yield for example of wheat using the parameters described above as independent variables, can be formulated mathematically as:

$$Yield_{wheat} = b_0 + b_1*NDVI(t) + b_2*GSR(t) + b_3*GF + b_4*SDD(t) \quad (2),$$

where $Yield_{wheat}$ is the vector of all measured wheat−yield data, NDVI, GSR, GF and SDD are the corresponding vectors of the derived parameters, and t is the prediction date. This leads to a set of regression coefficients $\{b_0,b_1,b_2,b_3,b_4\}$, which then can be used for predicting crop yield on other wheat−paddocks. Table 3 shows the squared correlation coefficients for wheat using a multiple linear regression of yield to different combinations of independent variables and for the three prediction dates examined.

One can see from table 3, that adding parameters generally improves correlation. Considering all examined crops, certain parameter combinations can be identified, that deliver “optimum” results for the three prediction dates examined. For “10. Sep.” that is {NDVI, GSR}, as the GF parameter is not available that early in the growing season. For the other dates the combinations are {NDVI, GSR, GF} for “$NDVI_{max}$”, and all of the parameters examined for “31. Oct.”. The correlation figures for canola and cereals (wheat and barley) all lie in a similar range. However, the correlation coefficient does not give information on the actual quality of a prediction using the set of derived regression coefficients $\{b_0,b_1,...,b_n\}$. The prediction model was then evaluated.

Table 3: Squared correlation coefficients for different combinations of independent variables to yield of wheat at three prediction dates using a multiple linear regression.

95-97				
Date	NDVI	NDVI,GSR	NDVI,GSR, GF	NDVI,GSR, GF,SDD
10. Sep.	0,420	0,558	n/a	n/a
NDVI max	0,633	0,681	0,723	0,733
31. Oct.	0,497	0,720	0,720	0,737

4. MODEL EVALUATION AND DISCUSSION OF THE RESULTS

Using the “optimum” parameter combination for the prediction dates, the multiple regression model was evaluated by removing data−records from the database, calculating regression coefficients with the remaining records and using those coefficients for modeling the yield of the removed records. The residuals then can be analyzed statistically.

Table 4 summarizes the residual analysis based on single data−records for the three crop types examined. The sum of the residuals squares, is a measure for the overall error being made. Due to the various count of data available for the different crop types, it can only be used as a relative measure within one crop type. Predictions at “$NDVI_{max}$”delivered the best results. This is due to the fact, that “$NDVI_{max}$”is a variable date depending, for example, on sowing date and crop development. The relative errors lie below (wheat and cereals) or around 20 % (canola). Although the local farmers of the Eastern Wimmera confirm that these results are in the order of their estimates based on knowledge and experience, it is difficult to compare both kinds of “predictions” with each other. To get an idea of the crop yield they can expect, they also use the empirical equation

Table 4: Results of the residual analysis based on single data−records, using the optimum”parameter combinations.

Optimum	res. anal.; single paddock			tons / ha
Pred. Date	Canola	Wheat	Cereals	
10. Sep.	0,34	0,61	0,61	avg.
	23,62	19,09	20,69	% error
	0,04	0,43	0,17	st.dev.
	0,68	1,69	1,85	max.
	2,66	16,59	21,66	sum res. sq.
NDVI max	0,30	0,52	0,45	avg.
	21,23	16,14	15,02	% error
	0,04	0,37	0,09	st.dev.
	0,52	1,26	1,22	max.
	2,19	12,00	11,35	sum res. sq.
31. Oct.	0,21	0,54	0,48	avg.
	14,76	16,94	16,17	% error
	0,05	0,17	0,10	st.dev.
	0,83	1,74	1,71	max.
	2,57	13,81	13,30	sum res. sq.

$$Y = x * (GSR – E) / 1000, \qquad (3)$$

where Y is yield, x is an empirical coefficient, depending on the crop type, GSR is the growing season rainfall and E is the evaporation (personal communication with local farmers). GSR and E values at the end of the growing season are estimated at the prediction dates, based on the conditions before. Table 5 shows the results using this approach with measured GSR and estimated E for the years examined, assuming, that GSR is known in advance, as is not in reality. One can see, that using the multiple linear regression model, the results of the predictions are better in all cases. This does not proof the statistical model to be superior to the farmers estimates, but it shows, that the results are likely to be as good as their estimates or better.

Table 5: Results of the residual analysis using the GSR approximation (equation 3).

1995–1997	residual analysis; GSR approximation			tons / ha
Pred. Date	Canola	Wheat	Cereals	
10. Sep.	0,43	0,63	0,58	avg.
	30,20	19,76	19,53	% error
	0,12	0,20	0,16	st.dev.
	1,16	1,95	1,48	max.
	5,23	17,77	19,86	sum res. sq.
NDVI max	0,45	0,61	0,57	avg.
	31,52	19,08	19,36	% error
	0,13	0,21	0,12	st.dev.
	1,01	1,69	1,30	max.
	5,53	17,21	18,06	sum res. sq.
31. Oct.	0,35	0,57	0,51	avg.
	24,43	17,89	17,02	% error
	0,08	0,21	0,14	st.dev.
	0,81	2,36	1,85	max.
	3,32	15,89	15,73	sum res. sq.

Table 6 shows the residual analysis for wheat at the “optimum” parameter combinations, examining whole year’s data. As the database comprises three years only (1995 to 1997), this test is not of great statistical value, especially as the agrometeorological conditions between the years were quite different. Nevertheless, some trends can be seen. The average yield of wheat on the test paddocks was 3.9 t/ha in 1995, 3.5 t/ha in 1996 and 2.0 t/ha in 1997. In 1995 and 1997 yield was systematically overestimated for all prediction dates, except “$NDVI_{max}$. The reason therefore can be found within the data: In 1995 on the 10th of September as well as on the 31st of October the differences in the values of NDVI and rainfall compared to those of 1996 are quite significant, while the differences in the yield values are not that high. 1996’s

Table 6: Results of the residual analysis for wheat at the optimum”parameter combinations, examining whole year’s data.

Wheat	residual analysis, whole year’s data			tons / ha
Pred. Date	1995	1996	1997	
10. Sep.	1,91	0,89	1,13	avg.
	48,93	25,24	57,07	% error
	0,87	0,16	0,41	st.dev.
	4,24	1,80	2,00	max.
NDVI max	0,48	0,66	0,98	avg.
	12,30	18,72	49,49	% error
	0,19	0,18	0,23	st.dev.
	1,28	1,54	1,70	max.
31. Oct.	0,82	0,69	1,56	avg.
	20,90	19,43	78,90	% error
	0,41	0,15	0,19	st.dev.
	2,14	1,36	2,04	max.

data compared to 1997's data shows both, a great difference in values and in yield. This might be due to non−linearity effects, but non−linear regression could not be proved statistically for the whole database by testing diverse kind of fits. Taking 1995's data out of the database and modeling its yield using regression coefficients derived from the remaining data−records, hence, must lead to an overestimation. The same is valid for the modeling of 1997's yield, while 1996 yield is slightly underestimated. This fact shows, that this model needs testing with additional data from a longer observation period. For the prediction date "$NDVI_{max}$ the residual analysis shows no systematical over− or underestimation throughout 1995 to 1997. Again, the reason for this is the fact, that "$NDVI_{max}$ is not a fix prediction date, like the others. All that also underlines the importance of the "GF" parameter, as it is a time variant measure as well. This is confirmed by the fact that the error being made at the prediction date 10.Sep. without"GF"is much higher than the one made at "31.Oct.".

5. CONCLUSION

It was the aim of this study to test the applicability of the NOAA−AVHRR in combination with meteorological for crop yield estimation in the Eastern Wimmera, South−Eastern Australia.

It was shown, that the parameters NDVI, GSR, GF and SDD, correlate with grain yield of wheat, cereals (wheat and barley) and canola. Three, for the farmers important prediction dates were examined, the 10th of September, the date of the maximum NDVI value in the NDVI−MVC curvature and the 31st of October. Yield estimates using the linear regressions of the single parameters are not accurate enough for the Farmers' requirements. Therefore the parameters were included into multiple linear regressions as independent variables to predict grain yield. This significantly increased correlations, and yield estimations at the prediction date "$NDVI_{max}$"could be made with an accuracy in the order of the farmers' estimates, or better. It is obvious that this model needs further examination. The inclusion of additional data and a longer observation period, where more diverse agrometeorological conditions are taken into account, will probably improve the results. Also, the quality of the data used certainly can be improved by an enhanced processing setup. Tests with 1998's data, however, made another major shortcoming of this model apparent. 1998 was affected by frosts late in the growing season end of October and beginning of November (!), that is after the prediction dates. This results in an overestimation of grain yield by 1 to 2 t/ha, as none of the effects caused by the frost days is reflected in the independent variables. Bad weather conditions or diseases occurring after the predictions, therefore, are not taken into account by this model. Due to the large subsets used, the environment of the observed paddocks has to be uniform. If this is not the case, for example due to small water−bodies, no reliable predictions are possible. If the remote sensing data can be derived from smaller subsets, also the accuracy of the method described might increase. Further investigation is necessary, before the described model can become an useful farming tool. If the results are at least confirmed, and an operational setup can be implemented, the method has the potential to benefit the farming community in South Eastern Australia. The relatively simple and easily accessible data used, might allow the model to be applied to other regions in the world with minor modifications.

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